

Bayesian Data Cleaning for Web Data

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ABSTRACT

Data Cleaning is a long standing problem, which is growing in importance with the mass of uncurated web data. State of the art approaches for handling inconsistent data are systems that learn and use conditional functional dependencies (CFDs) to rectify data. These methods learn data patterns—CFDs—from a clean sample of the data and use them to rectify the dirty/inconsistent data. While getting a clean training sample is feasible in enterprise data scenarios, it is infeasible in web databases where there is no separate curated data. CFD based methods are unfortunately particularly sensitive to noise; we will empirically demonstrate that the number of CFDs learned falls quite drastically with even a small amount of noise. In order to overcome this limitation, we propose a fully probabilistic framework for cleaning data. Our approach involves learning both the generative and error (corruption) models of the data and using them to clean the data. For generative models, we learn Bayes networks from the data. For error models, we consider a maximum entropy framework for combining multiple error processes. The generative and error models are learned directly from the noisy data. We present the details of the framework and demonstrate its effectiveness in rectifying web data.

1. INTRODUCTION

Real-world data is noisy and often suffers from corruptions that may impact data understanding, data modeling and decision-making. This situation is ubiquitous and even more severe when we deal with the web data generated by users or automated programs. For example, humans can introduce errors like *typos* and *omitted* data entries, and automated approaches can introduce algorithmic errors such as *inaccurate* information extraction. Alleviating this problem needs data cleaning, i.e., catching and fixing corruptions in the data. In this paper, we focus on unsupervised cleaning for the uncurated structured data on the web rife with incompleteness and inconsistency. By identifying and curing noisy values, it is possible to gain deeper understanding of the data, improve models, or make better decisions.

A variety of approaches have been proposed for data cleaning, from traditional methods (e.g., outlier detection [9], noise removal [15], and imputation [7]) to recent effort on examining integrity constraints, e.g., functional/inclusion dependencies (FD/IND) [3] and their extensions (CFD/CIND)

[5, 2]. Although these methods are efficient in their own scenarios, they have severe drawbacks when cleaning the noisy web data because: (1) State of the art approaches (e.g., [3, 5, 2]) depend on the availability of a clean data corpus or external reference table to learn data quality rules/patterns before fixing the errors. Such clean corpora may be easy to establish in a tightly controlled enterprise environment but infeasible when on the web. One may attempt to learn data quality rules directly from the noisy web data. Unfortunately, as we will demonstrate in Section 3, this attempt fails to obtain any rules even with very small percentage of corruptions in the data; (2) Many other approaches (e.g., [9, 15]) are only concerned about identifying or removing noise (corruptions) rather than fixing them; (3) Some of the prior work (e.g., [10, 7]) only focuses on fixing a single type of error. This is inadequate on the web where multiple different kinds of corruptions could happen.

We answer the web data cleaning problem by devising an end-to-end probabilistic framework on the available web data which involves learning a model of the clean data generation process as well as an error model of the corrupting process that introduces the noise. Then, by treating the clean value as a latent random variable, our framework leverages these two learned models and automatically infers its value through a Bayesian estimation. There are several advantages to this framework. First, modeling data probabilistically allows our framework to tolerate possible noise in the training data¹. In other words, it relaxes the limiting requirement in the existing approaches (i.e., building clean corpus in advance for learning deterministic data quality rules). Second, explicitly and naturally modeling the noise and the data corruption process through an error model improves the accuracy and robustness of the noise identification and fixing. For example, our error model can consider a wide spectrum of errors that occur commonly on the web (e.g., misspelling, replacement and deletion errors). On the contrary, most state-of-the-arts have to characterize each type of errors and develop cleaning strategy for them separately. This is especially inconvenient when a new type of error is found or the noisy data contains multiple types of errors.

We evaluate the proposed framework rigorously on a real-world dataset (used auto sales data). The results demonstrate the effectiveness and efficiency of our method with respect to different sizes of the data and various levels of noise in the data.

To summarize, our main contributions are as follows:

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¹We assume only a small portion of the data is corrupted while the majority is clean.

1. We find that although CFD-based approaches are designed to capture and fix dirty data, ironically, learning CFDs however depends on the availability of a perfectly or largely clean data corpus. Through the empirical experiment, we show that CFD learner fails to discover any CFDs from a dataset which contains a very small percentage of noise (0.1%). Such discovery, to the best of our knowledge, has not been explored before, hence it is new.
2. We propose an end-to-end probabilistic framework for cleaning the dirty web data. Our approach involves learning both the data generative model and error (corruption) model from the input dirty dataset. For a possible corrupted tuple, our framework leverages these two learned models and then automatically infers its value.
3. We conduct extensive experiments to evaluate the effectiveness and efficiency for our framework. The experiments are performed on a real web dataset with different types and levels of corruptions introduced.

The rest of the paper is organized as follows. In Section 2 we discuss related work. Section 3 presents the performance of CFD-based approaches on real noisy web data. In Section 4 we present our approach. Quantitative evaluations are described in Section 5. We conclude the paper in Section 6.

2. RELATED WORK

Recent years have witnessed a significant research interest in data cleaning and enhancing data quality. A variety of approaches have been proposed with focus on noise elimination, missing value prediction, and noisy value correction. Some of them work directly on detecting and removing data corruptions but without fixing them, such as outlier detection [9] and noise removal [15]. On the other hand, some focus on fixing those corruptions alone, such as value imputation [7]. More recently, integrity constraints-based approaches have been proposed to capture and fix data corruptions such that the resulting database D' is either consistent and minimally differs from original database D or certain errors in D get fixed. These methods heavily use the editing rules which are generated from the (conditional) functional dependencies (CFDs or FDs), (conditional) inclusion dependencies (INDs or CINDs) or matching dependencies (MDs) found from the data [3, 5, 2, 14].

The focus of most of the above works is to improve the quality of the data from a closed domain (e.g., census data or enterprise data) with a single type of error (either incompleteness or inconsistency). Therefore, it is not clear whether applying them to the noisy data on the web will work. This is because of the openness of the web where many kinds of errors may co-exist. Furthermore, most integrity constraints-based approaches require rules which are deterministic and carefully tuned. However, given the uncertainties on the web, the performance of these approaches cannot be guaranteed. More importantly, learning editing rules requires a clean training corpus of high quality (an implicit assumption made in most of the work in this line, see discussions in Section 3). However, such corpora are infeasible to acquire on the web. To tackle these limitations, in this paper, we propose an end-to-end probabilistic frame-

work which is designed to handle the data cleaning problem for the web data.

3. LIMITATIONS OF CFD-BASED METHODS FOR CLEANING WEB DATA

In this section, we present a understanding of how CFD based approaches work on real web data and show their inabilities to clean the web data. As an example, Figure 1 shows the performance of a conditional functional dependency (CFD) learner on the real auto sales data with respect to different levels of noise (e.g., spelling errors, deletion errors, or replacement errors), which are generated randomly. The schema for this dataset is `car(model, make, car-type, year, condition, drive-train, doors, engine)` and the total number of tuples was over 30,000. For the CFD learner, we directly used the one provided by the authors of [4].

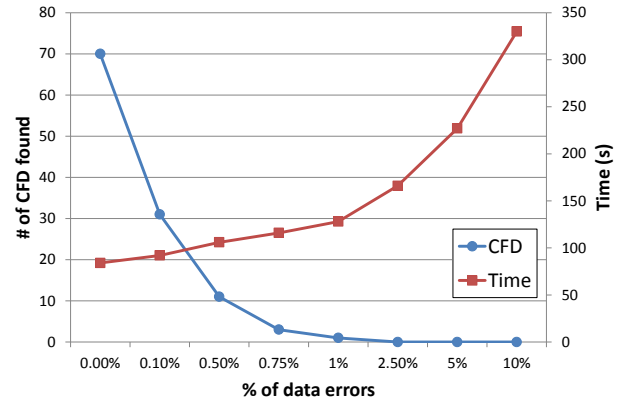


Figure 1: Learning CFD from dirty web data. It is clear that #CFD decreases but time increases w.r.t the growth of data errors

Based on the graph, we make one key observation of the deficiency of CFD: with the growth of percentage of errors in the data, CFD dramatically finds fewer data editing rules. In specific, with only 1% errors in the data, the system is unable to learn any rules. As a result, the error data is basically not cleanable or unrepairable. We believe this is mainly due to the fact that: (1) the presence of corrupted values violates possible patterns in the data, making them fractional and inconsistent; (2) On the other hand, finding CFD is deterministic [4], i.e., CFD cannot tolerate any errors in the data patterns without any approximations.

We find that the CFD-based methods only work well if the data is perfectly clean or largely clean (e.g., CFD learner found 70 or 31 rules when data is 100% or 99.9% clean as shown in Figure 1). However, such assumption is rather unrealistic when we try to clean the real web data since the web is open and its noise rate would be possibly much higher than any controlled closed domain (e.g., enterprise database) which itself was reported to have an average 5% data errors [12]. Besides, CFD-based approaches are mostly used to make the data consistent (i.e., data patterns after cleaning tend to conform to these CFD rules). However, it is not guaranteed that these fixed errors are the certain errors. To obtain the certain fixes, recent effort [6] suggests to first acquire a clean master data, learn CFD there and apply the learned rules to clean data. Unfortunately, while these clean corpus might be easy to establish in a closed domain, it is

hard to do so on the web.

4. OUR APPROACH

The observation mentioned above highlights the importance of developing approaches that can really clean certain errors in dirty web data. In this section, we describe our model and the approach we propose to solving this problem.

4.1 Conceptual Model

In this work, we view the data cleaning task as a statistical inference problem. Let $\mathcal{D} = \{T_1, \dots, T_n\}$ be the input dataset. T_i is a tuple with m attributes $\{A_1, \dots, A_m\}$, which can be either clean or dirty, i.e., one or more attributes values are corrupted. Let $\mathcal{T}^* = \{T_1^*, \dots, T_n^*\}$ be a correction candidate set for a tuple T . Then, in order to clean T , the model is to find the most likely T^* in \mathcal{T}^* (note that T^* can be as same as T if T is a clean tuple):

$$T^* = \arg \max_{T^* \in \mathcal{T}^*} \Pr[T^* | T] \quad (1)$$

In practice, instead of directly optimizing Equation 1, we can solve an equivalent problem by applying Bayes' rule and dropping the constant denominator. So that we have:

$$T^* = \arg \max_{T^* \in \mathcal{T}^*} \Pr[T | T^*] \Pr[T^*] \quad (2)$$

So what is $\Pr[T | T^*]$ and $\Pr[T^*]$? To answer this, let us first review how a tuple gets corrupted. We can view tuples T as being generated by a two-stage process. First, in the generation stage, a (noise free) tuple T^* is generated according to an underlying “clean” probabilistic data model. Then, this tuple gets corrupted. Which attribute(s) are corrupted is determined by an underlying probabilistic “error” model and the “dirty” values for the corrupted attribute(s) are generated from that error model according to some probabilities. The actual representation stored in \mathcal{D} (and seen) is the tuple T . Therefore, $\Pr[T^*]$ can be viewed as the “clean” data generative model and $\Pr[T | T^*]$ can be viewed as the probabilistic “error” model. We summarize this error generation process in Figure 2.

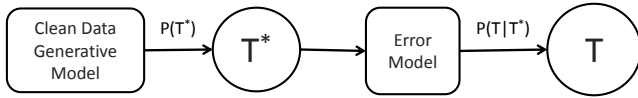


Figure 2: Conceptual model of our approach

A benefit of our approach based on generative and error models is its flexibility. For example, we can make the error model accommodate a wide spectrum of possible errors (a common limitation of current data cleaning approaches is to focus on single type of errors). Furthermore, one can create an error model to account for either dependent or independent corruptions.

Now, given the two models, our task is to estimate them. We start with learning the generative model using Bayes networks and later building error model with a maximum entropy model.

4.2 Data Generative Model

Calculating the data generative model $\Pr[T^*]$ needs to consider the dependencies between the attributes of possible clean tuple T^* . Bayes network seems to be a good choice to model and quantify these correlations.

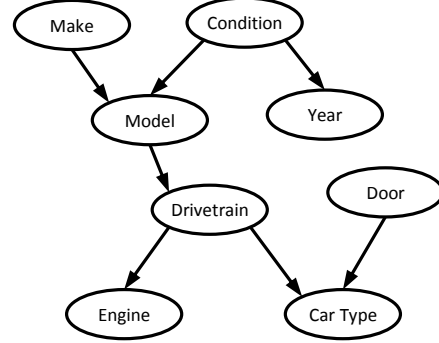


Figure 3: The learned Bayes Network structure of Auto dataset

Learning the Bayes Network usually involves two steps: learning the topology of the Bayes network and learning its conditional probability tables (CPTs). For the first step, we use the Bayesian learning package *Banjo* [8] and run it over the dataset \mathcal{D} . Note that although \mathcal{D} may contain noisy data, but unlike CFD approaches, Bayes network naturally models the data in a probabilistic way and thus can tolerate such noise. Once we have the structure of the Bayes network \mathcal{BN} , we use *Infer.NET* package [11] to learn the parameters (aka conditional probability tables). The Bayes network thus learned represents $\Pr[T^*]$ in a factored form. In particular, the probability of any specific true tuple T^* can be read off as a joint probability entry from the Bayes networks. In Figure 3 we show a sample of the Bayes network structure learned from the auto dataset.

4.3 Error Model

Next, we need to estimate the probabilistic error model $\Pr[T | T^*]$. To simplify the learning of the error model, we assume that each attribute is corrupted independently of the other attributes. This allows us to learn the tuple error model as a product of the attribute error models. Specifically, we have:

$$\Pr[T | T^*] = \prod_{1 \leq i \leq m} \Pr[T_{A_i} | T_{A_i}^*] \quad (3)$$

As mentioned earlier, the error distribution described by our error model, $\Pr[T_{A_i} | T_{A_i}^*]$, is general enough to represent any kind of error, as long as the distribution is known. In this paper, we focus on three types of errors that we observed to be the most commonly occurring in the web data: spelling errors, replacement errors, and deletion errors. We present different strategies to characterize them, a summarization is presented in Equation 4.

$$\Pr[T_{A_i} | T_{A_i}^*] = \begin{cases} 1 & \text{if no error} \\ f_{ed}(T_{A_i}, T_{A_i}^*) & \text{if spelling error} \\ f_{ds}(T_{A_i}, T_{A_i}^*) & \text{otherwise} \end{cases} \quad (4)$$

The error distribution of a spelling error is based on the edit-distance feature f_{ed} (see its definition below). Otherwise, our estimation is based on the distributional similarity

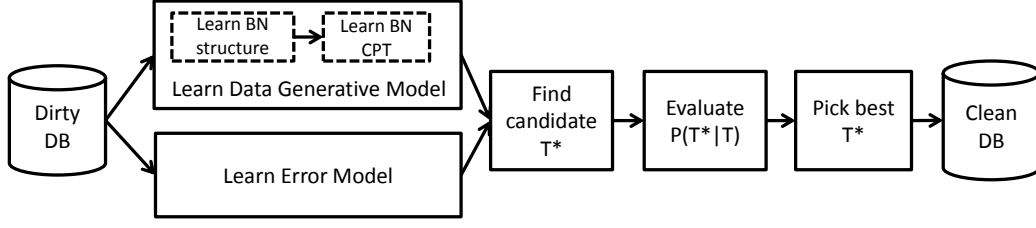


Figure 4: The architecture of end-to-end probabilistic web data cleaning system. Our framework requires both data generative model and error model from the raw data. As mentioned in Section 4.2, learning data generative model is based on a two-stage process as depicted in dashed boxes, respectively.

feature f_{ds} (see its definition below). In such a case, the error model $\Pr[T_{A_i}|T_{A_i}^*]$ can be regarded as the probability that one attribute value $T_{A_i}^*$ is replaced by other value T_{A_i} . Note also that we can view a deletion error as a special case of the substitution error, i.e., the substituted value is empty (NULL value).

Definition 4.1 (*Edit-distance feature*). This feature f_{ed} is defined based on string edit-distance between two input tuple values. To present it in a probabilistic way, we use the definition in [13]:

$$f_{ed}(T_{A_i}, T_{A_i}^*) = \exp\{-ED(T_{A_i}, T_{A_i}^*)\} \quad (5)$$

where $ED(T_{A_i}, T_{A_i}^*)$ is the number of edit operations required to transform attribute value $T_{A_i}^*$ into T_{A_i} .

Definition 4.2 (*Distributional similarity feature*). This feature f_{ds} is defined based on the probability of replacing one value with another under a similar context. Formally, we have:

$$f_{ds}(T_{A_i}, T_{A_i}^*) = \sum_{c \in C(T_{A_i}, T_{A_i}^*)} \frac{\Pr[c|T_{A_i}^*]\Pr[c|T_{A_i}]\Pr[T_{A_i}]}{\Pr[c]} \quad (6)$$

where $C(T_{A_i}, T_{A_i}^*)$ is the context of a tuple attribute value, which is a set of attribute values that co-occur with both T_{A_i} and $T_{A_i}^*$. $\Pr[c|T_{A_i}^*] = (\#(c, T_{A_i}^*) + \mu) / \#(T_{A_i}^*)$ is the probability that a context value c appears given the clean attribute $T_{A_i}^*$ in the sample database. Similarly, $P(T_{A_i}) = \#(T_{A_i}) / \#\text{tuples}$ is the probability that a dirty attribute values appears in the sample database. We calculate $\Pr[c|T_{A_i}]$ and $\Pr[T_{A_i}]$ in the same way. To avoid zero estimates for attribute values that do not appear in the database sample, we use Laplace smoothing factor μ .

The following example illustrates how distribution similarity between features is computed.

Example 4.1 Consider a tuple t : (*Focus, Honda, JPN, Mid-size, V6*) from group 4 (g_4) in Table 1, where the frequencies are based on the occurrences of certain attribute-values. e.g., 100 tuples (such that they form a group) whose $\text{Model}=\text{Accord} \wedge \text{Make}=\text{Honda} \wedge \text{Size}=\text{Full-size} \wedge \text{Engine}=\text{V6}$. Based on common knowledge, the value *Focus* might be dirty.² There are two possible candidates for the correct value: *Accord* from g_1 or g_2 , and *Civic* from g_3 . To determine which is the right one, we calculate distributional similarity features $f_{ds}(\text{Accord}, \text{Focus})$ and $f_{ds}(\text{Civic}, \text{Focus})$.

First, we need to get the context $C(\text{Accord}, \text{Focus})$. Note that, since there are two groups of *Accord* car with different

²Focus is well-known Ford car.

engines, the result of their distributional similarity to *Focus* in t is also different. Nevertheless, let S_1 be the set of all the attribute values in the tuples that contain *Accord* from g_1 . We have $S_1 = \{\text{Honda, JPN, Full-size, V6}\}$; Similarly, we have $S_2 = \{\text{Honda, JPN, Full-size, V6}\}$, where S_2 is the set of co-occurring attribute values of tuples that contain *Focus* in g_4 (since t is from g_4). Let the context $C(\text{Accord}, \text{Focus}) = S_1 \cap S_2 = \{\text{Honda, JPN, Full-size, V6}\}$. Applying Equation 6, we can get $f_{ds}(\text{Accord}, \text{Focus}) = 0.179$ conditioned on g_1 and g_4 . Analogously, we can also get $C(\text{Civic}, \text{Focus}) = \{\text{Honda, JPN}\}$ and $f_{ds}(\text{Civic}, \text{Focus}) = 0.082$. As a result, *Accord* is the right candidate for dirty value *Focus*.

Table 1: Sample database

GID	Model	Make	Orig	CarType	Engine	Freq.
g_1	Accord	Honda	JPN	Full-size	V6	100
g_2	Accord	Honda	JPN	Full-size	V4	150
g_3	Civic	Honda	JPN	Mid-size	V4	100
g_4	Focus	Honda	JPN	Full-size	V6	15
g_5	Focus	Ford	USA	Compact	V4	105

In practice, we do not know beforehand which kind of error has occurred for a particular attribute. In other words, it is impossible to predict that definitely without knowing the clean version, $T_{A_i}^*$. Furthermore, it is also rather unrealistic to have a single definite error strategy for a given attribute of a tuple. In fact, we want a unified error model which can accommodate all three types of errors (and be flexible enough to accommodate more errors when necessary). For this purpose, we use the well-known maximum entropy framework [1] to leverage all available features, including string edit distance-based feature f_{ed} and distributional-based feature f_{ds} . So for each attribute A_i , we have our unified error model defined on this attribute as follows:

$$\Pr[T_{A_i}|T_{A_i}^*] = \frac{1}{Z} \exp\{\alpha f_{ed}(T_{A_i}^*, T_{A_i}) + \beta f_{ds}(T_{A_i}^*, T_{A_i})\} \quad (7)$$

where α and β are the weight of each feature. $Z = \sum_{T^*} \exp\{\sum_i \lambda_i f_i(T^*, T)\}$ a normalization factor. To compute the entire error model for tuple T and T^* , we just plug Equation 7 in Equation 3.

4.4 Putting the Pieces Together

We now describe the working of the system depicted in Figure 4. Our system runs as a standalone application on an offline database which may contain possible corruptions. We first tokenize the entire data and applying the Banjo package to learn the structure of the Bayes network for it. We then provide the learned structure together with the entire database to an inference engine (Infer.NET in our paper) for learning the CPTs. By completing this stage, we

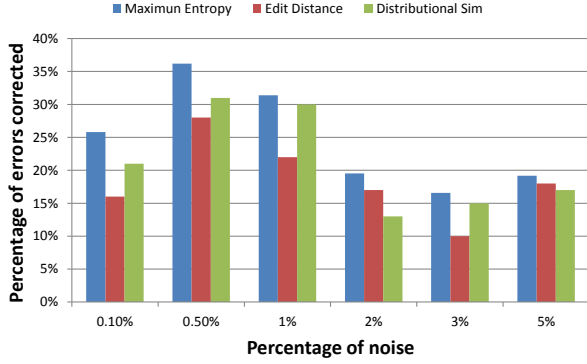


Figure 5: The percentage of corrupted values cleaned by the algorithms (using both features, only edit-distance feature, and only distributional similarity feature) as a function of the noise in the database.

have a generative model of the data. In parallel, we define and learn an error model which incorporates three types of errors (call Section 4.3). Now we can begin cleaning the database tuple by tuple. For each tuple T in the database, we first find a set of its clean candidate $\mathcal{T}^* = \{T_1^*, \dots, T_i^*\}$ by looking at all the tuples in the database that are within a certain edit distance of T . Then, for each $\langle T, T^* \rangle$ pair in the database, we now compute the $\Pr[T^*|T]$ value using Equation 2 which itself is based two learned models as mentioned above.

Last, we pick the one which maximizes $\Pr[T^*|T]$ and deem it the best T^* and store it as the clean copy of the tuple.

5. EXPERIMENTS

In this section, we quantitatively study the performance of our proposed approach on a large real datasets: Used car sales data. We present two sets of experiments on evaluating the approach in terms of (1) the effectiveness and (2) the efficiency.

5.1 Experimental Setup

To perform the experiments, we obtained the real data from the web. The first dataset is *Used car sales* dataset D_{car} which contains around 10,000 tuples crawled from Google Base. The schema of this dataset that we used in our experiments was $\text{car}(\text{model}, \text{make}, \text{car-type}, \text{year}, \text{condition}, \text{drive-train}, \text{doors}, \text{engine})$. We manually inspected the data to make sure it was clean and deemed the dataset “clean”. We then introduced three types of noise to attributes in D_{car} . To add noise to an attribute, we randomly changed it either to a new value which is close in terms of string edit distance (distance between 1 and 4, simulating spelling errors) or to a new value which was from the same attribute (simulating replacement errors) or just delete it (simulating deletion errors). Such “dirty” dataset is referred to as “ D'_{car} ”. We used a parameter τ ranging from 0.1% to 5% for the noise rate.

5.2 Effectiveness

We now show the effectiveness of our algorithm in cleaning the noise data in D'_{car} , and demonstrate how the parameters may be varied to obtain the desired results. In Figure 5 we show the resilience of the algorithm to noise in the input database D'_{car} . The weight (α) for the string

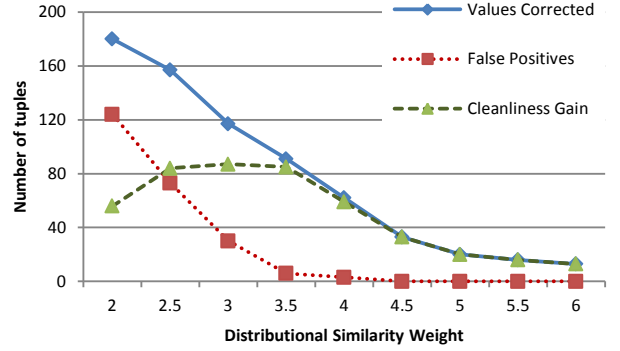


Figure 6: The number of values corrected by the algorithm, the number of erroneous values introduced by the algorithm, and the overall increase in the number clean values generated. The x-axis shows the value of the parameter.

edit distance feature f_{ed} was fixed at 2.3 while the weight (β) for the distributional similarity feature f_{ds} was fixed at 3.5. These values were chosen based on the results from Figure 6, which we explain in the next paragraph. In addition, to evaluate the effectiveness of the maximum entropy model that we adopted, we compare its cleaning performance with the ones obtained by the cleaning algorithms that use one single type of features at a time (in other words, we set $\alpha = 0$ and $\beta = 0$ in Equation 7 respectively and get accordingly results). As we can see from this figure, all algorithms achieve substantial reduction in the noise of the data. Specifically, at 1% noise in the data, our algorithm which leverage all features corrects more than 31% errors in the data, whereas CFD based methods failed to find even a single CFD (call Figure 1) and are thus not able to fix any data corruptions. The number of false positives for each of these cases was less than or equal to 11 tuples (which is a very small percentage of the corpus size). Besides, it is clear that using the maximum entropy model from to combine all features achieves better results than using them alone.

Setting β : Recall that in our approach we have two weights that can be adjusted: the weight given to the distributional similarity (β), and the weight given to the edit distance (α). The ratio of these two weights depends on which kind of error is more likely to occur. We found that setting the edit distance weight to $0.667 \times \beta$ yields the best results. Keeping this ratio fixed, in Figure 6, we show how the algorithm performs as β is changed. The “values corrected” data points in the graph correspond to the number of attribute values that were erroneous in the input data that the algorithm successfully corrected (when checked against the ground truth).

The “false positives” are the number of legitimate values that the algorithm changed to an erroneous value. When cleaning the data, our algorithm chooses a candidate tuple based on both the prior of the candidate as well as the likelihood of the correction given the evidence. Low values of the parameter β give a higher weight to the prior than the likelihood. In other words, a lower value of the parameter indicates a higher likelihood of changing the tuple. As a result, some legitimate tuples are “corrected” to a tuple that has a much larger prior. As β is increased, the number of

such false positives reduces. However, this also reduces the number of values corrected, because some kinds of unlikely errors no longer justify the higher cost of correction.

The “overall gain” in the number of clean values is calculated as the difference of clean values between the output and input of the algorithm. In this particular experiment, there were 357 errors in the input data, of which the best correction was obtained at a parameter value of 3.0, where the overall gain was 87 clean values.

5.3 Efficiency

In Figure 7a and Figure 7b we show the time taken by the algorithm (using Maximum entropy. This graph includes both the time taken to learn the generative model as well as the time taken to clean every tuple of the database. As can be seen, the algorithm completes in a reasonable amount of time, even with 10,000 tuples in the database.

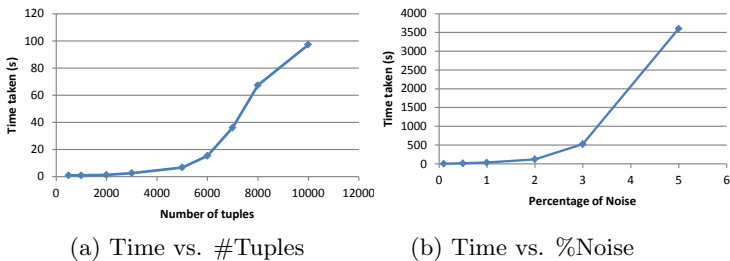


Figure 7: Time taken by the algorithm to clean the database. In (a) we fixed with 0.5% data noise; In (b) we fixed #Tuples=5k.

We show the effect of noise on the time taken by the algorithm in Figure 7b. For this curve, the number of tuples was kept constant at 5,000 tuples. As can be seen from the figure, the time taken by the algorithm increases as the percentage of noise in the data increases. This is because for every tuple that we have to clean, we have a much larger set of candidate T^* s to consider. Adding noise to the dataset effectively increases the number of different tuples within the edit distance threshold of the data, thus a much larger number of error model comparisons need to be made.

6. CONCLUSION

In this paper, we focused on approaches for cleaning inconsistent web data. We showed that the current state of the art approaches, which learn and use conditional functional dependencies (CFDs) to rectify data, do not work well with web data as they demand clean master data for training. We proposed a fully probabilistic framework for cleaning data that involved learning both the generative and error (corruption) models of the data and using them to clean the data. For generative models, we learn Bayes networks from the data. For error models, we consider a maximum entropy framework for combining multiple error processes. The generative and error models are learned directly from the noisy data. Preliminary experimental results on web data showed that our probabilistic approach is able to reduce errors in the data long after CFD-based methods fail to be effective.

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